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Optimizing the Abandonment of a Technological Innovation

Albert Joseph Parvin Jr. * and **Mario G. Beruvides**

College of Engineering, Texas Tech University, Lubbock, TX 79409, USA; mario.beruvides@ttu.edu
* Correspondence: albert.parvin@ttu.edu

Abstract: The primary objective of this study is to reveal macro-level knowledge to aid the optimization, evaluation, and strategic planning of technological innovation abandonment. This research uses an exploratory data analysis (EDA) approach to extract directional and associative patterns (macro-level knowledge) to assess technological innovation abandonment optimization. Deterministic and stochastic simulations are employed to reveal the impact of three factors on abandonment optimization, namely, a technological innovation's diffusion rate, a technological innovation's probability of achieving a given diffusion rate, and the point of abandonment. The patterns and insights revealed through the graphical examination of the simulation provide associative and directional knowledge to assess the abandonment optimization of technological innovation. These revealed patterns and insights enable decision-makers to develop an abandonment assessment framework for optimizing, evaluating, and proactively planning abandonment at the macro level.

Keywords: technological innovation; abandonment optimization; diffusion rate; S-curve; technological innovation diffusion; macro-level

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1. Introduction

This research effort is the second in a series of endeavors that are part of a research thrust to build and develop macro-level knowledge to aid resource decision-makers in making informed, proactive decisions on when to abandon a technological innovation. The first exploration [1] examined the boundaries and likelihoods of the diffusion rates of technological innovations. This current endeavor builds and adds to the body of knowledge by exploring the impact of three factors on abandonment optimization, namely, a technological innovation's diffusion rate, a technological innovation's probability of achieving a given diffusion rate, and the point of abandonment. We characterize these factors through deterministic and stochastic simulations to reveal patterns and insights for abandonment optimization assessment.

Technological innovation is defined in various ways in the scholarly literature; it is thus essential to establish an operational definition to bound this research. Technological innovation is defined here as a new (minor or major) or improved product, process, or device that results in the commercialization of new or improved goods (products or services) or a new or improved product or service production process [2–4]. This operational definition is important because it guides the measuring, quantifying, and tracking of technological innovation via market diffusion sales data, enabling the study of technological innovation abandonment optimization from a macro perspective. The phrases technological innovation and innovation are used interchangeably in this paper.

Time, cost, and other resource constraints limit the quantity and quality of information, including abandonment information, to decision-makers. As a result, directional and associative patterns (macro-perspective knowledge) of a decision area are often the only tools available to prevent a decision-maker from just making a random guess. As an analogy, it is easy to tell if a cup of coffee is hot (macro-level) but more difficult to tell its exact temperature (microlevel). Both macro- and micro-perspective level examinations provide valuable, meaningful, and actionable information; however, macro-based information is often easier to understand, acquire, and interpret. The macro-perspective examination of abandonment optimization, developed herein, provides associative and directional knowledge, which gives decision-makers general rules (guardrails and safety catches) for abandonment assessment. In terms of systems thinking, identifying these associative and directional patterns enables the understanding and simplification of complex situations and interrelationships [5–7]. By leveraging the boundaries and likelihoods of the diffusion rates of technological innovations, we determined macro-based benchmarks regarding the impact of the three factors on the optimal point of technological innovation abandonment.

This research explores developing general assessment guidelines for innovation abandonment, revealed through deterministic and stochastic-based simulations. The assessment insights developed herein enable decision-makers to proactively assess and manage the economic impact of technological innovation abandonment concerning time. An organization's understanding of and proactive use of time is a competitive advantage for growth and advancement [8–10]. In other words, a macro-based understanding of factors impacting the optimization of technological innovation abandonment has implications for the economics of an organization by improving its ability to make proactive, knowledge-based decisions in a timely manner. The patterns and insights for abandonment optimization assessment revealed herein give decision-makers easy to apply, easy to understand, and practical knowledge to proactively support effective technology end-of-life assessment.

This effort uses an exploratory data analysis (EDA) approach to uncover macro-perspective patterns and insights on technological innovation abandonment. We selected this method because there were a limited number of scholarly works in this research area, and the method is well-suited to summarizing and characterizing patterns and trends [11–13]. Specifically, this paper aims to address and expand the following research questions and reveal data patterns in the process.

- Question #1: What is the probabilistic optimal point of abandoning an incumbent technological innovation, assuming reinvestment (transitioning from an incumbent to a new candidate), if the incumbent technological innovation's diffusion rate is known, but the candidate technological innovation's diffusion rate is unknown?
- Question #2: What is the probabilistic optimal point of abandoning an incumbent technological innovation, assuming reinvestment (transitioning from an incumbent to a new candidate), if both the incumbent and candidate technological innovations' diffusion rates are unknown?

2. Background

Technological innovation forecasting and assessment are often used to determine whether technological innovation is worthy of pursuing, but they are not often thought of as a means to signal when the innovation has reached maturity or when it should be abandoned [14–20]. Much of the research on the assessment of technological innovation abandonment focuses on examining microlevel stimuli factors for abandonment. These stimuli factors can be grouped as innovation push (emergence of new and better innovations) and market pull (demand for new innovations) [21]. Although these factors are essential to consider, they are reactive in nature and require resource-intensive micro-based investigations that are often narrowly focused on a specific technological innovation. Stimuli factors can also be challenging to measure accurately or at all. As a result, micro-based abandonment assessment investigations are complex, challenging, and time-consuming to develop. As such, there is much to be gain in the expansion of the knowledge on technological innovation abandonment; and the work reported herein is designed to increase this knowledge from a macro perspective. To further clarify the decision maker's understanding of this research, we establish the meanings of the common terms and concepts that characterize it in the following paragraphs.

2.1. Abandonment, Obsolescence, and Withdrawal

Concerning technological innovation resource and investment management, there are numerous intermeshed definitions of the terms abandonment, obsolescence, and withdrawal (and their associated derivatives) that appear in the research literature. It is necessary to consider these terms and their connections and, more importantly, establish operational concepts of each for this research endeavor to provide scope and understanding of the focus of this effort. The word abandonment implies a control or intent (proactive) action, whereas obsolescence implies the result of actions or triggers (reactive). Similarly, withdrawal implies a controlled action. Thus, technological innovation abandonment is the act of withdrawing purposefully from an innovation investment, while technological innovation obsolescence results from becoming obsolete. Although the study of technological innovation obsolescence is important, it is out of the scope of this exploratory analysis.

The examination of technological innovation abandonment from the standpoint of maximizing an organization's resource investment is key to this research. Accordingly, the literature review for this effort focused on technological innovation abandonment decision tools and resource investments. The principal focus of the research literature was on the adoption of emergent innovations. As established, the research and development of abandonment decision tools are unsurprisingly limited [18]. The existing technological innovation abandonment research concentrates on reactive external (specific microlevel) causes of abandonment, termed "triggers" in the literature [18,22]. Common abandonment external triggers noted in the literature include alternative innovation superiority, adopter's feelings toward incumbent innovation, and perceived value (efficacy) of the candidate innovation by the adopter [18,22,23].

While a multitude of scholarly works examines the micro-perspective (i.e., pull and push) of technological innovation abandonment, this research aims to expand abandonment knowledge from the macro, systems perspective point of view. Specifically, a systems perspective understanding of the impact of the three assessment factors (a technological innovation's diffusion rate, a technological innovation's probability of achieving a given diffusion rate, and the point of abandonment on the overall assessment of abandonment optimization. However, to provide a comprehensive knowledge-based framework surrounding innovation abandonment, it is important to acknowledge and review the micro-perspective literature for isomorphic insights.

In terms of investment abandonment (innovation/technology efficacy), several micro-based decision models exist. Two such models are the Robicheck and Van Horn (RVH) [24] and Dyl and Long (DL) [25] models. Both models examine reactive investment abandonment from the framework of the asset value (trigger). The RVH model demonstrates that resources in terms of assets should sometimes be abandoned, even though they may still generate positive cash flows, based on their abandonment value [26]. The DL model shows that the abandonment decision model must consider the timing of abandonment value (time-value) to maximize the investment [26]. Both the RVH and DL models demonstrate how early abandonment of an asset can impact an organization's bottom line [27]. Gaumnitz and Emery [26] further expand on the DL model, demonstrating that the abandonment decision can be impacted via the replacement investment assumptions, such as capital investment interest differences between the abandoned incumbent innovation and the replacement candidate innovation. These micro-perspective-based tools provide insights into developing macro-perspective (system) assessment guidelines, such as the importance of understanding the time impact effects of abandonment. Therefore, one aspect of this research was to leverage the concept of maximizing time-value and the importance of considering the candidate replacement in abandonment optimization.

The field of obsolescence forecasting examines the diffusion lifecycle for patterns and trends (micro and macro perspective) using forecasting methodologies to enable management predictions for when a product or component is anticipated to become obsolete [28]. Planned obsolescence converts the passive nature of obsolescence into a control action, similar to abandonment; it is a business strategy that discounts an innovation purposefully to reduce the time between repeat investments and to maximize profits [29,30]. A key takeaway from obsolescence forecasting tools is using the diffusion lifecycle model to gain macro-perspective insights. Thus, this exploration into the assessment of technological innovation abandonment utilizes the diffusion lifecycle model to develop macro-perspective insights.

Concerning planned withdrawal in business and organization management planning, a harvesting strategy plan is an intentional organizational management withdrawal approach to respond to external conditions. It is the controlled, orderly withdrawal from a market with the intent of increasing cash flow and maximizing gains through reinvestment [31]. The harvesting strategy extends the abandonment model from a single event to a series of events: the transfer of resources from one investment to another. It also illustrates the impact on gain optimization of the business unit being withdrawn from, juxtaposed with the unit resources are being transferred to, as demonstrated by Martensson, A. and P. Valiente [32]. Based on the harvesting strategy, we view the abandonment model as a series event, extending the abandonment model from a singular event (no effects from the external environment, no reinvestment) to a series of events (external factors). From a macro-perspective, the abandonment of one technological innovation (the incumbent) for reinvestment into another technological innovation (the candidate) is defined for this endeavor as a series event.

2.2. Innovation Diffusion Model

Technological innovation diffusion models follow an S-curve. Frequently used S-curve models are the logistic model, Gompertz model, and Bass model [33–36]. We chose the logistic model because it is widely used to analyze innovation diffusion, and it is the cornerstone of these and other models in the research literature [37–43]. In addition, the Bass and Gompertz models can be derived from or be reduced to special forms of the logistic model [44–48]. While the advantages and disadvantages of each diffusion model are well studied, the adaptability, simplicity (in estimating parameters and extracting patterns from observed data), and informative nature of the logistic model make it foundational to macro diffusion examination [49,50]. Additionally, in the case of mature technological innovations, such as those with an extensive set of historical adoption market data through their lifecycles, the diffusion parameter differences between models tend to be good fits and yield similar results [51].

The mathematical formulation of the logistic model, used for innovation and technology growth, is shown in Equation (1) [52]:

$$Y(t) = \frac{C}{1 + \mathrm{a}e^{-rt}} \tag{1}$$

where: C (carrying capacity) is the limit to growth or the maximum diffusion ceiling, a (initial condition constant) is a constant determined by an appropriate initial condition, r (diffusion rate constant) is the growth rate constant, and t (time-variable) represents time.

2.3. Economic Measure

In finance and economics, there are numerous measures that decision-makers can use to determine the value of an investment. One such example is the time value of money (TVM), a primary foundational concept taught in engineering economics and used by decision-makers to determine if an investment is worth pursuing. According to the TVM, money in the present has a greater value than the value of the same sum received at the moment in the future due to money's potential to grow in value over a given period via investment and interest earned. Thus, TVM analysis is often used to determine when to select one investment over another. Although TVM is a robust and useful tool for determining when to invest in technological innovation, when used in abandonment decisions, it cannot provide insight regarding the impact of time. For example, if one is told the present value of innovation A is $1, no insight is given in relation to time. TVM addresses the value of money concerning time, but the inverse, the valuation of time (units measured per unit of time), is lost in its output [53].

An alternative way to measure the cost of goods and services (including innovation investments) is in terms of a standard that does not change (e.g., time) [54]. Diffusion time value (DTV) is a technological approach that assesses an innovation's viability in terms of time value [53]. DTV is expressed graphically in Figure 1 and mathematically represented by Equation (2). DTV is the diffusion percentage difference from initial entry to its exit at abandonment divided by the time difference from its initial entry to exit.

$$DTV = \frac{Y(t_{exit}) - Y(t_i)}{t_{exit} - t_i} \tag{2}$$

where: $Y(t_{exit})$ is the diffusion percentage at the time of abandonment, $Y(t_i)$ is the diffusion percentage at the time of initial investment, t_i is the time of the initial investment, and t_{exit} is the time at abandonment.

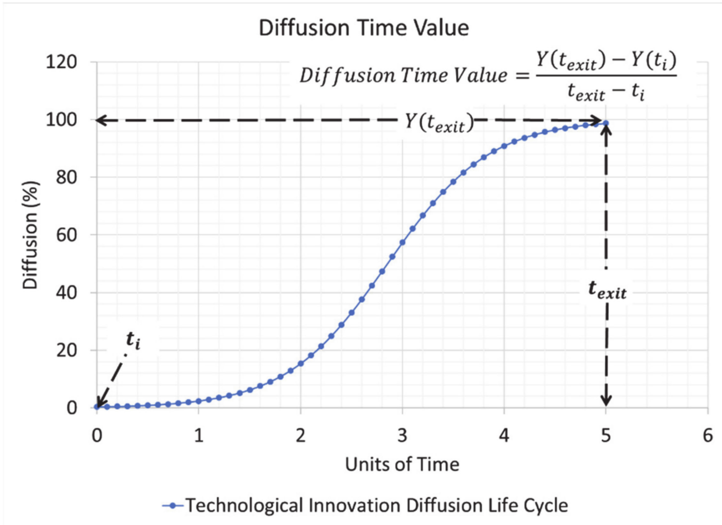

Figure 1. Diffusion time value (DTV) illustration.

DTV is an expression of opportunity cost, for it represents the monetary cost of time (time value) up to the point of abandonment, and it can give decision-makers insights into the effects of abandonment along a technological innovation's diffusion lifecycle. Concerning decision analysis, planned abandonment decisions ideally are thought of as future proactive events. DTV is a rate or a ratio of output to input; in terms of abandonment decisions, the diffusion percentage captured is the output (or benefit) in relation to a technological innovation's S-curve (lifecycle) captured per time unit spent. For example, if one is told the DTV of abandoning technological innovation A after capturing 75% of its diffusion lifecycle is 25% per year, insights on the value of time are gained. Additionally, if a decision-maker further calculates that the DTV of abandoning the same innovation after capturing 90% of its diffusion lifecycle is 15% per year, the impact of capturing an additional 15% (90% minus 75%) more market would decrease the benefit to cost ratio (DTV) by 10% per year. In terms of abandonment, the insights into time-value can enable decision-makers to effectively plan for maximizing gains and minimizing losses [53].

Parvin Jr, A. J. and M. G. Beruvides [53] demonstrated a link between time-based economics and DTV. Multiplying the market value (representing the maximum carrying capacity) by DTV yields value per unit time. As a result, DTV supports a basic corollary between time-based economic gains or losses at abandonment with the diffusion rate of an innovation [53]. As such, the diffusion point that maximizes the DTV is the optimal time value point of abandonment. As an example, for a singular event, a technological innovation's optimal diffusion point of abandonment is resolved as approximately 84% for a lifecycle based on the logistic model (when the initial entry diffusion is assumed to be zero as with a new investment), regardless of its diffusion rate.

3. Research Methodology

We used an EDA approach to gain a better systems perspective understanding of the impact of factors affecting the optimization of abandonment. Central to an EDA approach is the patterns and insights revealed through a graphical examination of the data obtained by exploring the research questions posed. An EDA emphasizes the fundamental understanding and identification of data relationships to build foundational knowledge, comprehension, and insight. It also provides a starting point for developing new working hypotheses and models for future testing [11–13]. To bound this effort, three assessment factors are examined. This effort used a simulation approach to study the correlational associations between these factors for assessing abandonment optimization. A simulation approach is a robust decision-making tool for it enables practitioners to view the system from multiple perspectives, provides improved system understanding and prediction, and facilitates the rapid exploration of alternative actions [55]. For this research effort, deterministic and stochastic-based simulation approach results are graphed and used to address the research questions.

3.1. Simulation Setup

Each constructed simulation herein used the logistic model to represent the diffusion of a technological innovation's lifecycle. The conditions defining the deterministic and stochastic-based simulation approaches are established in the following sections.

3.1.1. The Abandonment Event Form

In the context of this endeavor, and to give decision-makers a basis for the interpretation of the simulation results, it is important to define the simulation abandonment event form. This research endeavor's simulation approach used the series event concept, leveraged from the harvesting strategy and the RVH and DL models. A series event is defined as an event in which an incumbent technological innovation is abandoned, and the impact of the proposed candidate is not ignored, as conceptually illustrated in Figure 2. In practice, this event represents an organization's use of forecasting tools or practices for reinvestment. A singular event is defined as an event in which technological innovation is abandoned and future investment impacts are ignored (e.g., the event is isolated). In practice, this event represents one in which an organization lacks, ignores, or has inadequate forecasting tools or practices for reinvestment, resulting in poor abandonment optimization assessment. Although an interesting area of study, singular events are not included in this research.

To assess the impact of the factors on abandonment optimization for the deterministic approach, the incumbent's diffusion rate was fixed, and the candidate's was incrementally varied, as conceptually shown in Figure 3. To assess the impact of the factors on abandonment optimization for the stochastic approach, two series event variants of interest were defined and examined. The first series event variant (variant #1) assumed that the incumbent technology innovation's diffusion rate is known, but the candidate's diffusion rate is unknown, as conceptually illustrated by Figure 4. An analogous descriptive scenario to this variant is found in the card game blackjack. In blackjack, a player must choose to stand or take a card based on the cards they have and the dealer's visible face-up card, not knowing the dealer's hold card (face down card). A player can shift the odds in their favor by utilizing available information, such as the card deck has 52 cards, and the probability of drawing individually valued cards can be calculated. By knowing the diffusion rate of the incumbent and with a representative probability distribution of the candidate's diffusion rate, a decision-maker can make stochastic-based decisions. The second event variant (variant #2) assumes that the incumbent's and candidate's diffusion rates are both unknown, as conceptually illustrated in Figure 5. Both event variants utilize historical information on the probability of achieving a given technological innovation diffusion rate, which can be used as a starting point for decision-making. The diffusion rate boundaries for each approach are defined in the next section.

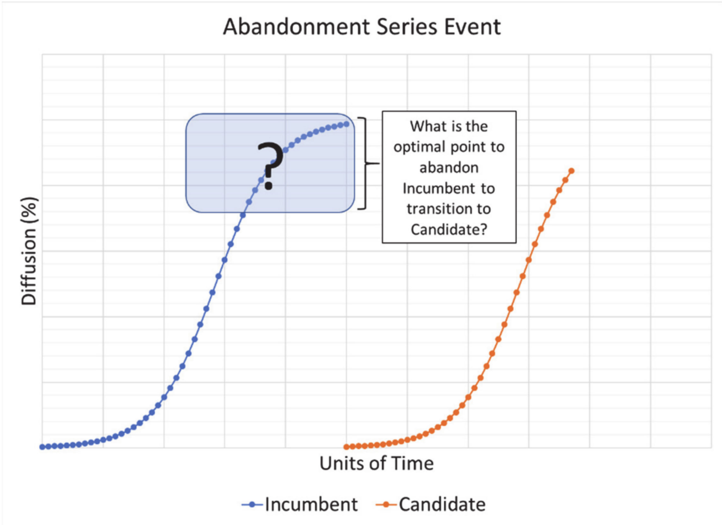

Figure 2. Incumbent to candidate abandonment series event illustration.

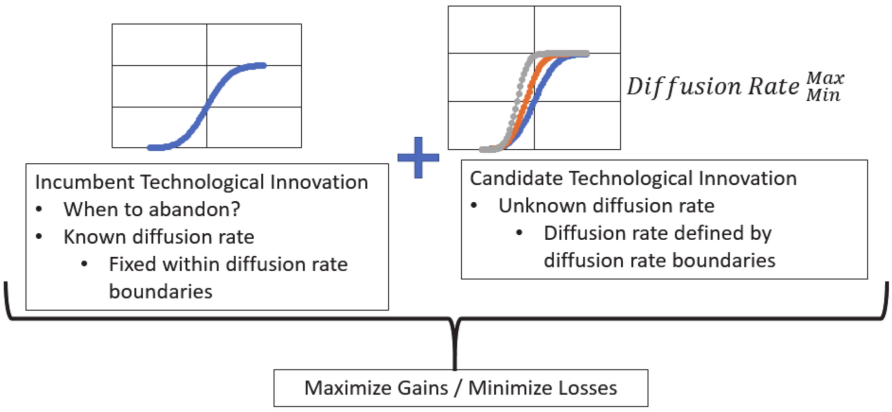

Figure 3. Deterministic simulation event form.

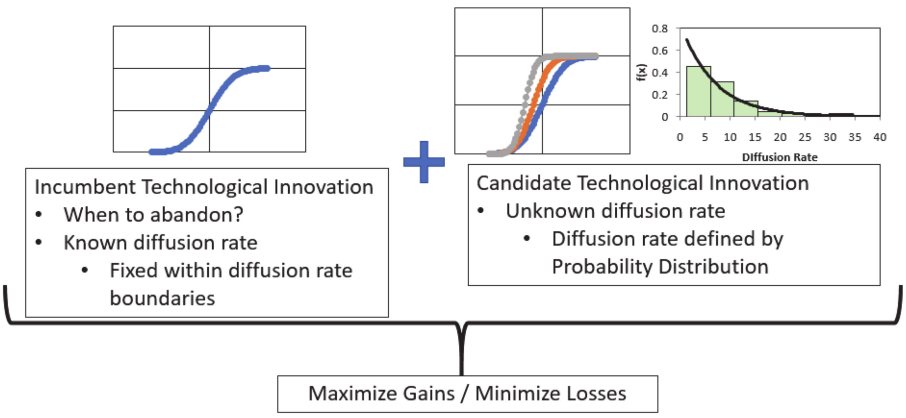

Figure 4. Stochastic simulation event form for series event variant #1.

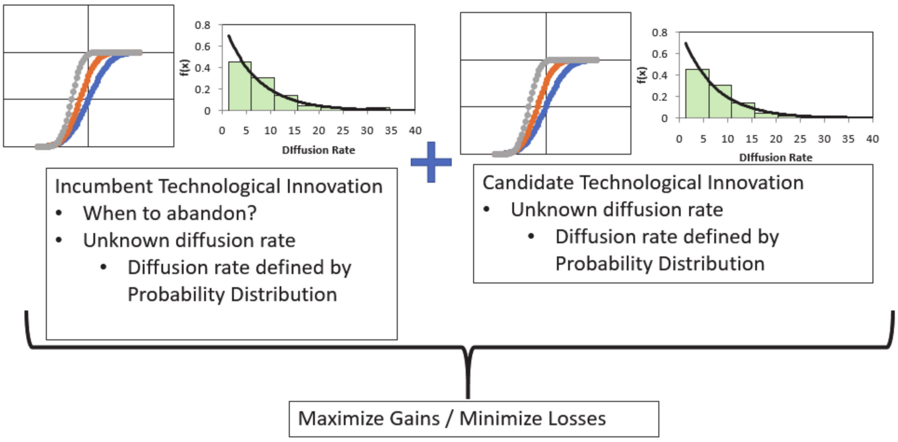

Figure 5. Stochastic simulation event form for series event variant #2.

3.1.2. Technological Innovation Diffusion Rate Bounding Range and Probability

To determine a meaningful representation of technological innovation diffusion rates for each simulation approach, previous research results were leveraged. Parvin, A. J. and M. G. Beruvides [1] conducted a macro-perspective study on the diffusion rates of technological innovations in which they examined the boundaries and likelihoods of US technological innovation diffusion rates. In their report, diffusion rate boundaries and potential representative probability density function models were outlined. The extracted associated minimum and maximum diffusion rate boundaries were 1.3% per year and 34.7% per year, respectively. These diffusion rates were used to bind the constructed deterministic and stochastic-based models developed herein to assess the optimal diffusion point of abandonment.

In addition, a maximum-likelihood estimation (MLE) analysis of 13 probability distributions on the data in the above-cited work, using goodness-of-fit (GOF) examination, determined that an exponential two-parameter distribution, with a λ of 0.146 and γ of 1.316, was a sound probability density function to represent technological innovation diffusion rates for macro-perspective studies [1]. Identifying a sound representative probability density function enables creating a model that expresses diffusion rates as a statistical expectation. The identified exponential two-parameter distribution was used to construct the stochastic-based simulation models developed herein. In addition, to add probabilistic context to the candidate's diffusion rate, the exponential two-parameter distribution will be overlaid on the deterministic simulation results to represent its likelihood.

3.1.3. Time-Based Economical Measure

As previously discussed, DTV gives decision-makers insight into the economic effects of abandoning an innovation in terms of time, an important factor for managing resources. To assess the optimal diffusion point at which to abandon the incumbent technological innovation (for a series event), the total DTV of the series was maximized by varying the incumbent's diffusion abandonment point, as conceptually illustrated in Figure 6.

The conditions listed in Table 1 define the series event and simulation parameters to allow for the maximization of DTV. Although numerous conditions can be envisioned in practice, these are a starting point for developing general assessment guidelines via macro pattern evaluation. In addition, the simulation approach established herein allows for the future evaluation of changes in these conditions.

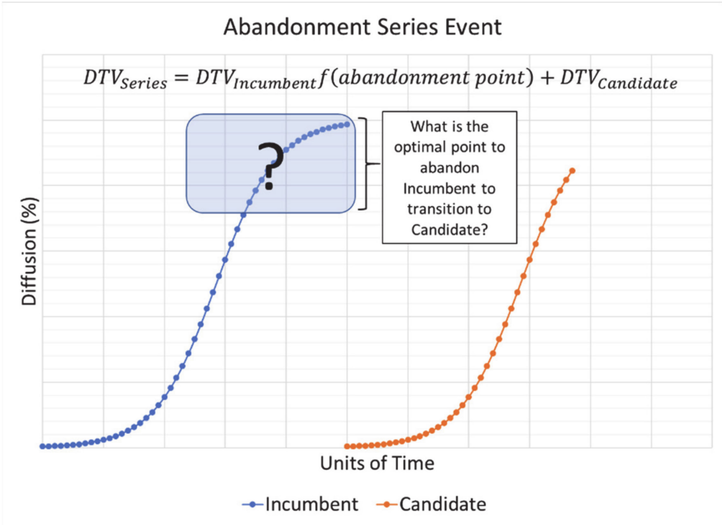

Figure 6. Total DTV of the series representation.

Table 1. Simulation condition parameters.

1. The maximum attainable diffusion (carrying capacity) of the incumbent is 100%
2. The minimum attainable diffusion (carrying capacity) of the incumbent is 50%
3. The candidate will not be abandoned before it reaches its optimal abandonment diffusion point for a singular event. 84% is the optimal diffusion point of abandonment for a singular event via DTV maximization analysis, using a logistic-based diffusion lifecycle
4. The incumbent and candidate start at 1% diffusion
5. One-year time intervals
6. Diffusion rate range: 1.3 to 34.7 percent per year (approximated as 1 and 35%)
7. There is no time delay between transitioning from the incumbent to the candidate
8. The total market values of the incumbent and candidate are equal

In terms of comparing an incumbent to a candidate technological innovation, the estimated total market value of each is required. We assume for this effort that the incumbent and candidate total diffusion economic values are equal. This assumption is justified in the spirit of developing generalized guidelines for assessing abandonment, as it enables a simplified initial foundation for the assessment of associative and directional relationships. The extension of the abandonment optimization model to examine technological innovations of unequal value is not within this effort's bounds. However, it warrants exploration and is noted as a recommended future topic of research.

3.2. Simulation Execution

The deterministic simulation, by definition, requires known inputs to determine a unique set of outputs for a defined model. The model was defined by the DTV of the series event, starting conditions, event conditions, and diffusion rate boundaries presented. The deterministic simulation approach utilized Microsoft Excel's generalized reduced gradient (GRG) solver to determine the optimal economic diffusion point of abandonment of the incumbent technological innovation (the output). Optimization was accomplished by solving the incumbent's diffusion abandonment point that maximized the total DTV of the series event within the defined conditions and boundaries. For the simulation inputs, the series incumbent's diffusion rate was fixed, starting with the minimum bounding diffusion rate and increased by one percent per year (up to the maximum diffusion rate) to resolve the optimal diffusion point of abandonment for each possible candidate diffusion rate, as outlined in Table 2. As indicated in Section 3.1.2, to add additional insights to the deterministic simulation results, probabilistic context will be mapped to the candidate's diffusion rate boundary range. The probabilistic context will be extracted from the exponential two-parameter distribution, previously determined by Parvin, A. J. and M. G. Beruvides [1] to be a reasonable probability density function for representing diffusion rates for macro-perspective studies.

Table 2. Deterministic simulation diffusion rates inputs.

Incumbent	**Candidate**
Diffusion rate % per year	Diffusion rate % per year
1	1,2,3, ... ,35
2	1,2,3, ... ,35
....	"
35	1,2,3, ... ,35

The stochastic simulation approach employed Microsoft Excel's generalized reduced gradient (GRG) solver to resolve the optimal economic diffusion point of abandonment of the series event variants. EasyFit (build 5.6) by MathWave Technologies, a data analysis tool, was used to generate high-quality random numbers from the probability density function selected to represent technological innovation diffusion rates, as outlined in this endeavor. EasyFit uses the Mersenne Twister algorithm, a proven method for generating pseudorandom numbers for statistical simulations [56]. A total of 56 and 114 simulation runs with random sample trials of 10,000 each were executed for each series event variant, respectively. The total sample run was determined using a standard error of the mean of less than 1%. This approach provides a normalized procedure to determine the number of iterations, and it bounds the accuracy of the simulation results [57,58]. Once stochastic diffusion rates were determined, the Microsoft Excel GRG solver was employed to determine the optimal economic diffusion point of abandonment of each series event variant within the starting conditions, event conditions, and diffusion rate boundaries defined herein.

4. Results

Using Microsoft Excel, deterministic and two stochastic simulation approach variations were constructed and executed to assess the optimal diffusion point to abandon the incumbent technological innovation. As noted, each technological innovation's diffusion lifecycle in the series was simulated using the logistic model. It was decided that both the incumbent and candidate technological innovation lifecycles would launch at 1% diffusion and that each would be bound by a diffusion rate range of 1.3 to 34.7 percent per year (approximated as 1 and 35%) as previously justified. These series events also assumed that there was no time gap between transitioning from incumbent to candidate; and that the abandonment of the candidate would occur at 84%, the optimal diffusion point of abandonment determined for a singular event via the maximization of the DTV for a logistic based diffusion lifecycle model. Microsoft Excel's GRG solver was used to determine the optimal economical diffusion point of abandonment of the incumbent technological innovation by maximizing the total DTV of the series event, using the incumbent's diffusion point of abandonment as the maximized variable.

4.1. Deterministic Simulation Results

The resultant deterministic surface map in Figure 7 shows the diffusion ranges to optimize abandonment, extracted by maximizing the total DTV based on the incumbent and candidate diffusion rates. The x-axis and primary y-axis represent the diffusion rates of the incumbent and candidate technological innovations, respectively. The surface bands constitute the optimal diffusion point of abandonment of the incumbent. As an example, if the incumbent technological innovation has a diffusion rate of 10% per year and the expected candidate has a diffusion rate of 4% per year, the optimal diffusion point of abandonment is around 90%. To add further context to the resultant deterministic surface map, the probability density function identified in Section 3.1.2 was leveraged to provide probabilistic information on the candidate's diffusion rate and is overlaid on the secondary y-axis. The secondary y-axis provides a basis for the probability of at least achieving the associated candidate diffusion rate. Utilizing this additional context and expanding on the previous example, Figure 7 additionally shows that there is approximately a 68% probability of the candidate at least achieving a diffusion rate of 4% per year.

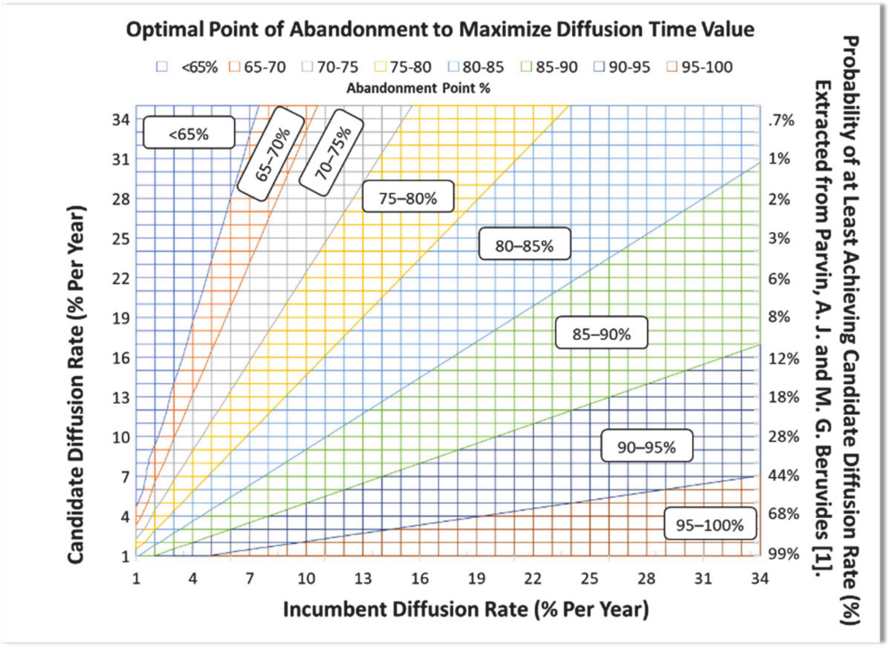

Figure 7. Surface map of optimized abandonment diffusion points for a series event.

4.2. Stochastic Simulation—Series Event Variant #1 (Representing Question #1) Results

Utilizing the exponential two-parameter probability density function, a total of 56 simulation runs, with random sample trials of 10,000 each, were executed to determine the probable candidate diffusion rates for the series event (variant #1). To formalize the series event's stochastic simulation for variant #1, incumbent diffusion rates, bound by the diffusion rate range defined previously and in increments of one percent per year, were then paired to these resultant probable candidate diffusion rates. The optimal diffusion abandonment point of the incumbent was then solved by maximizing the DTV of the formed series event for each trial pair. The resultant composite stochastic simulation of the average optimal point of abandonment for all the simulation runs, for series event variant #1, is shown in Figure 8. As an interpretive example, if the incumbent technological innovation has a diffusion rate of 10% per year and no information is known about the expected candidate's diffusion rate, the resultant stochastic-based optimal diffusion point of abandonment is around 87.5%. Bound by the diffusion rate range defined previously, the resultant abandonment optimal diffusion points ranged from about 61 to 95%.

4.3. Stochastic Simulation—Series Event Variant #2 (Representing Question #2) Results

To formalize the series event model for variant #2, an additional 58 simulation event runs were added to the existing 56 used for creating the variant #1 stochastic simulation. As noted, both the incumbent and candidate probable diffusion rates were represented using the exponential two-parameter probability distribution model. The combined 114 simulation event runs, yielding a standard error of the mean of less than 1%, were paired in groups of two (incumbent to the candidate) to model the diffusion rates of the series events of variant #2. This resulted in a total of 57 simulation pair (incumbent to the candidate) event runs forming the simulation, with random sample trials of 10,000 incumbents and 10,000 candidates each. Each series event pair was evaluated to determine the optimal diffusion abandonment point of the incumbent. This was accomplished by maximizing the DTV of the formed series events, using the incumbent's diffusion point of abandonment as the maximized variable. The average optimal diffusion point of abandonment for each simulation pair is shown in Figure 9. A subsequent average optimal diffusion point of abandonment of 81.8% was revealed for variant #2.

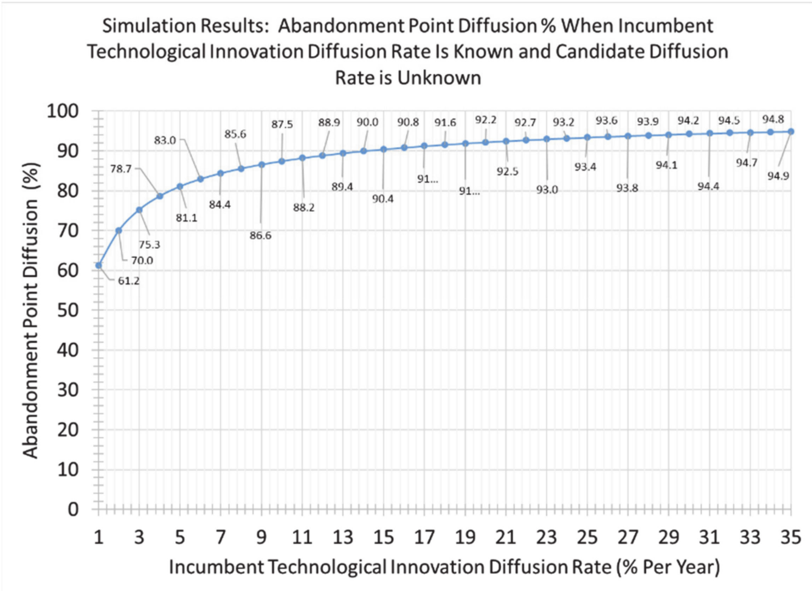

Figure 8. Resultant stochastic model—series event variant #1.

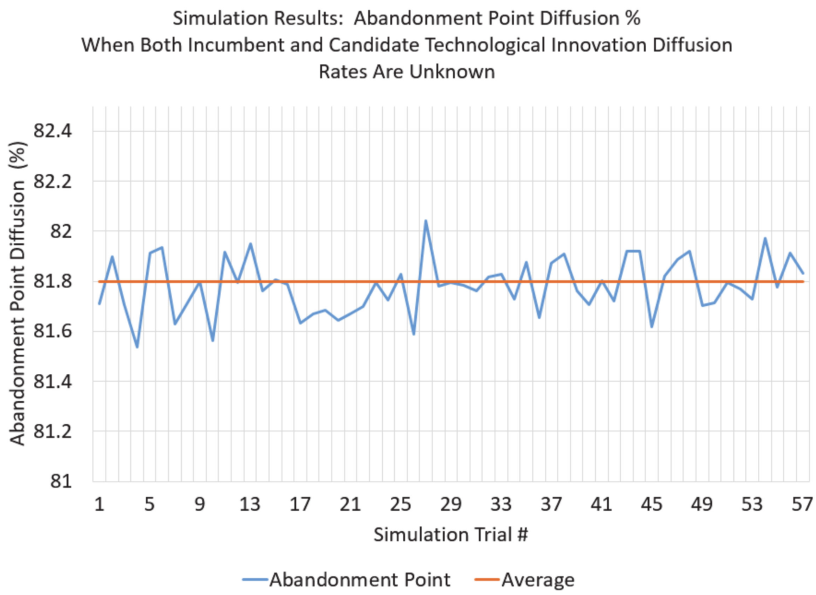

Figure 9. Resultant stochastic model—series event variant #2.

5. Discussion of Results

The primary purpose of this research was to build and develop general abandonment assessment guidelines from insights gained through examining the impact of three factors (a technological innovation's diffusion rate, a technological innovation's probability of achieving a given diffusion rate, and the point of abandonment) on abandonment optimization. Such guidelines would assist decision-makers in proactively assessing and managing the economic impact of technological innovation abandonment rather than reacting to it. To shape the discussion and interpretation of the results of this EDA effort, led by the research questions put forth in this effort, let us begin by examining the patterns revealed by the resultant deterministic and stochastic approaches generated for the series events under examination.

5.1. Deterministic Simulation Discussion

The deterministic resultant surface map shown in Figure 7 provides information on the optimized abandonment point ranges of the incumbent. If a decision-maker knows their incumbent's maximum diffusion rate and the candidate's desired maximum diffusion rate, even roughly, then optimized abandonment point ranges of the incumbent can be established for planning. Figure 7 also reveals this guideline: the higher an incumbent's diffusion rate, the narrower the probable optimal abandonment diffusion band. By way of illustration, if an incumbent has a diffusion rate of 34% per year, its optimal abandonment diffusion point ranges from approximately 84% to 99% for all likely candidate diffusion rates. Conversely, if the incumbent has a diffusion rate of 7% per year, its optimal abandonment diffusion point ranges from approximately less than 65% to 99% for all likely candidate diffusion rates. Decision-makers can use such a guideline for strategic planning.

In terms of risk, traditionally defined as a function of probability and impact, additional strategic information is gained from the enhanced overlaid context of the deterministic surface map's secondary y-axis, Figure 7. For example, if the incumbent has a diffusion rate of 31% per year and the candidate's desired diffusion rate is a minimum of 25% per year, abandoning the incumbent at the indicated optimal range of 80% to 85% would result in a high-risk of lost opportunity. The risk level can be assessed based on the probability of attaining the desired diffusion rate for the candidate. For this example, there is a low probability (3%) of at least attaining a 25% per year diffusion rate for the candidate; thus, the incumbent would likely be abandoned too early, resulting in a potential lost opportunity. Conversely, if the incumbent has a diffusion rate of 4% per year, and the candidate's desired diffusion rate is a minimum of 4% per year, abandoning at the indicated range of 80% to 85% could be considered lower risk, as indicated by the estimated 68% probability of at least attaining a 4% per year diffusion rate for the candidate. Strategies can be created using the probability of attaining a desired candidate diffusion rate to assess and gauge risk using the resultant deterministic surface map. Hence, the developed enhanced context deterministic surface map can be used to provide decision-makers with generalized abandonment assessment guidelines.

5.2. Stochastic Simulation—Series Event Variant #1 (Representing Question #1) Discussion

The stochastic approach graph for series event variant #1 (incumbent diffusion rate is known, candidate diffusion rate unknown), Figure 8, provides decision-makers with information on the optimized abandonment point of the incumbent based on its diffusion rate. The graph reveals an observed linearization trend of the optimal abandonment diffusion point as the incumbent's diffusion rate increases. This observed trend can be used to a decision-maker's advantage if there is uncertainty in the incumbent's diffusion rate when assessing abandonment. For example, the observed total spread of the optimal abandonment diffusion point is about 61% to 95%, as shown in Figure 8. Approximately 75% of this total spread (roughly 61% to 86%) is captured by technological innovations with diffusion rates of less than 9% per year. This pattern indicates that the accuracy of the incumbent's diffusion rate is less impactful on the optimal abandonment point as its rate increases.

Another interesting assessment pattern revealed from the stochastic approach for series event variant #1 is that technological innovations with low diffusion rates should not be abandoned immediately. For example, as bounded for this effort, the lowest possible abandonment diffusion point is 50%. The patterns exhibit that, even at the lowest diffusion rate bound by this study, the optimal diffusion abandonment point is 61.2%. It is a result of the incumbent being in the rapid growth phase of its lifecycle, whereas the candidate is at a slower, emerging stage. It would be expected that this pattern would change if the candidate were beyond its emerging stage, as would be the case if the incumbent and candidate diffusion lifecycles overlap.

5.3. Stochastic Simulation—Series Event Variant #2 (Representing Question #2) Discussion

As shown by the stochastic model for series event variant #2 (incumbent and candidate diffusion rates both unknown), graphically represented by Figure 9, the optimal diffusion abandonment point is approximately 81.8% diffusion for the defined boundaries of this endeavor. In terms of decision-making, abandoning the incumbent at 81.8% diffusion would yield the optimal result statistically over time. As a starting point, if a decision-maker has no information on either the incumbent or candidate, this result provides a sound basis for abandonment decisions. Regressed information is better than no information at all, for sound decision-making is driven by information, for without information, management and decision-making of any kind are no more than guesswork [59].

Additional decision-making knowledge is realized from the variant #2 stochastic simulation when compared to the variant #1 stochastic model outlined in this endeavor. For example, the extreme ends of the resultant optimal points from Figure 8 of variant #1, 61.2 to 94.5%, are only an approximately 29 to 15 percent difference, respectively, from the resultant optimal point of variant #2. Decision-makers can use this information along with their risk tolerance data to balance risks while maintaining the best chance of maximizing gains and minimizing losses. Although outside the scope of this effort, an examination of the standard deviation and variance of the optimal abandonment diffusion point of variant #2 would expand and strengthen a decision-maker's abandonment knowledge, and as such, deserves future examination.

To introduce and acknowledge the impact and sensitivity of the candidate's abandonment diffusion point on the stochastic results for series event variant #2, the stochastic model was rerun using 99% (set previously at 84%) as the point of the candidate's abandonment, with the result shown in Figure 10. As indicated in Figure 10, for the lowest and highest diffusion rate bound by this study, the optimal diffusion abandonment point increased to 63.5% (a 4% change) and 96.6% (a 2% change), respectively. These results indicate that, although the abandonment diffusion point of the candidate has an influence, its impact may be minimal. That said, this area warrants future sensitivity examination. In terms of assessing abandonment optimization, understanding the impact of assumption deviations can aid decision-makers in framing and weighing decision inputs based on criteria, such as confidence level.

5.4. Assumptions and Limitations

Given the macro-based perspective nature of this abandonment optimization assessment endeavor, assumptions and limitations must be acknowledged and addressed to provide context to the boundaries of this effort. These assumptions and limitations are listed and clarified below:

(1) All models used herein, including the diffusion model represented by the logistic model, are simplified representations of the real world. Rarely does raw diffusion data precisely align to a diffusion model. The power of a diffusion model lies in its proven ability to aid and enable the efficient generation of representative information to allow decision-makers and researchers to interpret data easily and identify patterns in that data [15,36,60–64]. As mentioned previously, the adaptability, simplicity, and informative nature of the logistic model were well-suited for macro-based studies.

(2) The probability distribution model used was derived from US technological innovation data. It has been demonstrated in other research that innovation diffusion can be affected by region. The expansion and merit of this research to other regions were out of the scope of this effort, but it warrants study in future research. The accuracy of the distribution model used should also be acknowledged, for it was

developed to obtain macro-based insights. Its absolute accuracy was not required for this effort because macro-based results were sought that were not definitive but rather associative and directional by definition. Nevertheless, examining the impact of error in the probability distribution model of diffusion rates warrants future study.

(3) In defining and optimizing the series event, several conditions were established, as listed in Table 1. Although this effort justified each condition, variations of these warrant future examination.

(4) The optimization of diffusion abandonment for this effort assumed that both the incumbent and candidate market values were equal. This study assumed that a decision-maker would want to invest, at a minimum, in a candidate technological innovation with a market value similar to the incumbent. Extension of the abandonment optimization model to examine technological innovations of unequal value also warrants future investigation. In addition, the results obtained in this effort are macro-based and not definitive but are instead starting points, associative and directional in nature.

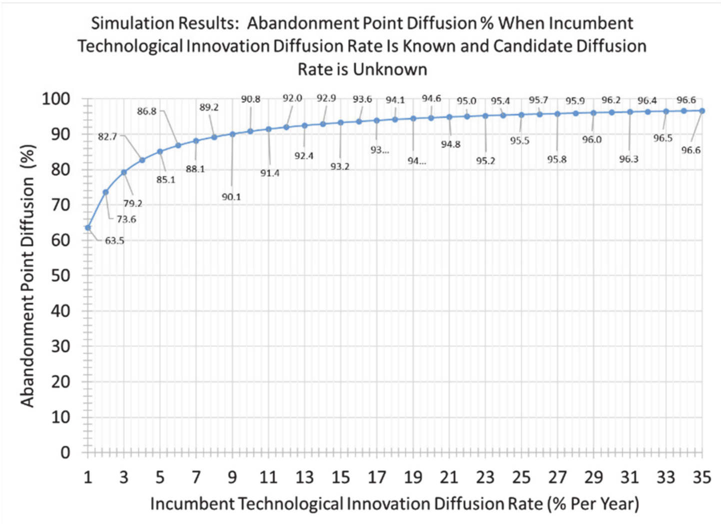

Figure 10. Resultant stochastic model—series event variant #2, assuming candidate's abandonment at 99% diffusion.

5.5. Practitioner Implications and Significance

This effort sought to develop macro-level knowledge to aid decision-makers in making informed, proactive decisions on when to abandon a technological innovation. The directional and associative patterns revealed via the EDA provide decision-makers a framework for assessing abandonment at a macro-level. The framework also provides general boundaries and decision points for making abandonment decisions using regressed macro-based information. In addition, three related implication areas warrant discussion.

5.5.1. Proactive Abandonment Decisions

The transformation of the abandonment of technological innovation from a reactive to proactive approach has significant implications for the resource management of an organization. It has been established that a proactive organization has a higher potential to maximize profits/growth and minimize losses and thus a higher propensity to surpass reactive organizations [65–67]. This endeavor strives to support, expand, and shift an organization's viewpoint on technological innovation abandonment from a reactive event to an event that can be controlled and even planned for proactively. The quantification and assessment of factors on abandonment optimization support proactive decision-making by providing decision-makers with general abandonment assessment rules and guidelines. The deterministic and stochastic approaches examined in this effort can provide useful knowledge and tools to assist decision-makers in successfully developing strategies for technological innovation abandonment.

5.5.2. Complexity Reduction and Decision Speed

By understanding the interdependency of a technological innovation's diffusion rate and its optimal abandonment point (in relation to time-based economics), a decision-maker can better develop strategies for simplifying decisions about abandonment and resources. The speed at which an organization makes decisions has been identified as a determinant of an organization's prosperity and growth [68–70]. At present, no such relational insights between diffusion rate and abandonment optimization exist in management or the research literature. In addition, previous research has supported that, as task complexity goes up, cognitive demand goes up, and as cognitive demand goes up, a practitioner will have an increased likelihood of not justifying the use of a complex decision-making strategy or tool, especially when time is a factor [71,72]. Both the base series deterministic and stochastic frameworks examined in this effort can, at a minimum, provide guidelines and easy-to-understand practical rules for the optimization, evaluation, and strategic planning of technological innovation abandonment.

By way of illustration, if a decision-maker knows the incumbent's diffusion rate, abandonment diffusion rate boundaries can be established for all likely diffusion rates of the candidate, including the likely probability of occurrence by using the deterministic series approach. In addition, if a decision-maker knows the incumbent's diffusion rate but has no information on a potential candidate's diffusion rate, an optimal abandonment point can be determined via the stochastic framework established for series variant #1. Furthermore, if a decision-maker has no information on either the incumbent's or candidate's diffusion rate, they can use the stochastic framework established for series variant #2 to determine an optimal abandonment point. These frameworks simplify and provide guidelines and easy-to-understand practical rules for decision-makers to be able to optimize, evaluate, and plan for technological innovation abandonment in a proactive manner. Consequently, forming a cornerstone for basing abandonment decisions, enabling decision-makers to speed decision-making and reduce complexity (reducing cognitive demand).

5.5.3. Systems Thinking

An organization's decisions are often made within a system (the whole is greater than the sum of its parts). However, abandonment decisions are often framed as either a push or pull event, overlooking the interconnection and interdependencies of these events. System patterns are often emergent, meaning that they cannot be predicted from knowledge of the factors; only when a system is examined from a macro perspective can factor interactions emerge [73]. By utilizing characteristics of the RVH and DL models and the harvesting strategy concept, we established the significance and impact of viewing the interrelationships of innovation abandonment as a series event. This can be seen through quantification of the candidate's diffusion rate impact on the optimal abandonment diffusion point; and in the probability assessment of achieving said candidate's diffusion rate; if both are ignored, a decision-maker might conclude that the optimal diffusion point of abandonment is approximately 84%, as is the case in a singular event, ignoring reinvestment and probabilistic information. As demonstrated in the deterministic model, the candidate diffusion rate impacts the optimal abandonment point. As a practical example, if an organization is invested in an incumbent innovation, knowing how impactful an incumbent's and candidate's diffusion rates are on abandonment optimization, even at a macro-level, creates meaningful knowledge for decision-makers. As such, organizations and decision-makers alike should seek to examine innovation abandonment decisions as a system, through the expansion of technological innovation abandonment from a singular event to a series of events, to maximize gains and minimize losses

6. Conclusions

In this research endeavor, both deterministic and stochastic-based simulation approaches were used to measure the impact of factors on abandonment optimization towards developing general assessment rules and guidelines. The extracted abandonment optimization results were examined for patterns and tendencies using an EDA approach. Generalized abandonment optimization patterns and trends were revealed through the visual examination of three assessment factors. These patterns and trends allow developing a simple abandonment assessment framework for optimizing, evaluating, and proactively planning abandonment at the macro level. Furthermore, the examination of abandonment decisions as a system (a series event) should be considered by decision-makers because that approach delivers a quantifiable impact on abandonment optimization.

Patterns and insights are foundational toward enabling system thinking in an organization, as they enable the understanding and elucidation of complex situations and interrelationships of technological innovation abandonment. The patterns and insights revealed herein provide associative and directional knowledge to assess the abandonment optimization of technological innovation. This includes, if a decision-maker knows the incumbent's diffusion rate but has no information on candidates, an optimal abandonment point can be determined via the stochastic framework established for series variant #1. Furthermore, if a decision-maker has no information on either the incumbent's or candidate's diffusion rate, they can use the stochastic frameworks established for series variant #2 to determine an optimal abandonment point. These frameworks elucidate and provide decision-makers easily comprehensible directional knowledge to assess abandonment optimization proactively.

A supported outcome of an EDA is the development and forwarding of new exploratory models for future testing in a research area through the examination of patterns and trends. As such, this endeavor forwards three new exploratory models to be considered in the future for this research area. First, the resultant enhanced deterministic surface map model of optimized abandonment diffusion points for a series event, Figure 7. Next, the two variant stochastic models addressed the principal research question of this effort. Stochastic model variant #1 addressed the probabilistic optimal point of abandoning an incumbent technological innovation, assuming reinvestment (transitioning from an incumbent to a new candidate) if the incumbent technological innovation's diffusion rate is known, but the candidate technological innovation's diffusion rate is unknown Figure 8. Stochastic model variant #2 addressed the probabilistic optimal point of abandoning an incumbent technological innovation, assuming reinvestment (transitioning from an incumbent to a new candidate), if both the incumbent and candidate technological innovations' diffusion rates are unknown, Figure 9.

Although this study contributes to the macro-perspective knowledge of technological innovation abandonment, we identified several potential areas for improving, strengthening, reinforcing, and expanding this research topic. These areas are discussed below.

(1) In situ innovation diffusion rate forecasting. The primary objective of this research endeavor would be to outline the components required to develop a framework for determining how accurately a technological innovation's diffusion rate can be forecast with partial diffusion data. It is easy for an organization to determine a technological innovation's diffusion rate in hindsight, but post-situ-based decision-making often leads to reactive rather than proactive action. A framework for gaining in situ knowledge about a technological innovation's diffusion rate would benefit an organization's decision-makers in proactively setting strategy, policy, and resource management.

(2) Extension of the abandonment optimization model to examine the impact of the incumbent and candidate lifecycle overlap. The primary objective of this research endeavor would be to expand the abandonment optimization model by exploring and introducing a variable to represent the overlap of an incumbent and candidate lifecycle as well as to quantify the impact of that overlap on abandonment optimization. The abandonment optimization model examined assumed as a starting basis that the

lifecycles of the incumbent and candidate did not overlap and that there was no gap in their transition. Quantification and characterization of the overlapping impact would serve to improve and expand the body of knowledge on abandonment optimization.

(3) Extension of the abandonment optimization model to examine technological innovations of unequal value. The primary objective of this research endeavor would be to expand the abandonment optimization model by exploring and introducing a variable to represent the potential unequal value of the incumbent and candidate on abandonment optimization.

(4) Examination of the economic impact of delaying or hastening abandonment from the optimal point of abandonment. The primary objective of this research endeavor would be to quantify the impact of delaying or hastening abandonment based on time-based economics. Such an effort would enable a decision-maker to determine the time-based economic impact of the speed at which decisions are made within an organization.

(5) Examination of the impact of error in the probability density function model of diffusion rates. The primary objective of this research endeavor would be to expand the abandonment optimization model by exploring the sensitivity of abandonment optimization to error in the probability density function model of diffusion rates. As all researchers know, no model is perfect, but by examining its sensitivity to variations, a model's robustness and limits can be deduced.

(6) Extension of the abandonment optimization model to examine its sensitivity to changes; specifically, the change of the abandonment diffusion point of the candidate's and the incumbent's minimum achieved diffusion percentage on the optimal diffusion point of abandonment.

(7) Examination of the standard deviation and variance of each series variant's optimal abandonment diffusion point.

In conclusion, the macro-perspective study of abandonment optimization has implications for the economics of an organization by improving the quality and speed of decisions made. This research expands existing and provides new macro-based insights into technological innovation abandonment, enabling the proactive engagement of decision-makers. The graphical outputs developed herein reveal directional and associative patterns that provide insights for decision-makers seeking to assess the abandonment optimization of technological innovation.

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